A Generalized Process Model of Human Action Selection and Error and its Application to Error Prediction

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Abstract

Our model of action selection and postcompletion error in two form filling tasks extends to skip errors in a story telling task. We also discuss how it explains perseverations in one of the aforementioned form filling tasks. Finally we discuss a predictive classifier application we built from the model's data. The classifier could allow an autonomous agent to know when it is a bad time to interrupt a human, when a human is about to err, and how to help.

Keywords: Cognitive Architecture; Action Selection; Human Error; Process Model; Predictive Model

Introduction

We are probably not saddled with special processes that make us err. If neuroscience could find the locus of such a curse, neurosurgery could cure us of the reason for the expression "to err is human." Instead it is more parsimonious for human error to arise naturally out of the same processes we use to select our correct actions. This is a story about how a process model of action selection we originally developed to explain postcompletion error in two form filling tasks also explains skip errors in a story telling task. The action selection model presented in this paper was originally used to explain postcompletion error in two form filling tasks (Tamborello & Trafton, 2013a & b). Other than some task-specific details it remains unchanged. It is part of a larger effort to establish a unified process-level action selection and error model. A unified framework is important because one cognitive system, i.e. the human mind, produces all error types as well as correct behaviors. Getting the explanation correct for one or more phenomena in one task then acts as a constraint on getting the explanation correct for other error types as well as correct action selection. Furthermore, if we are to predict error in complex task environments multiple error types must fall naturally out of the theory.

The model works within the framework of the ACT-R 6 cognitive architecture (Anderson et al., 2004). ACT-R is a hybrid symbolic and subsymbolic computational cognitive architecture that takes as inputs knowledge (both procedural and declarative about how to do the task of interest) and a simulated environment in which to run. It posits several modules, each of which perform some aspect of cognition (e.g., long-term declarative memory, vision). Each module has a buffer into which it can place a symbolic representation that is made available to the other modules. ACT-R contains a variety of computational mechanisms and the ultimate output of the model is a time stamped series of behaviors including individual attention shifts, speech output, button presses, and the like. It can operate stochastically and so models may be non-deterministic. One of the benefits of embodying a theory in a computational architecture, such as ACT-R, is that it allows researchers to develop and test concrete, quantitative hypotheses and it forces the theorist to make virtually all assumptions explicit. To the extent that the model is able to simulate human-like performance the model provides a sufficiency proof of the theory.

Our model also builds upon the Memory for Goals theory (Altmann & Trafton, 2002), which posits that we encode episodic traces of our goals as we complete tasks. Each goal is encapsulated in an episodic memory, which sparsely represents what was the current mental context at the time of its encoding. The strength of these memories decay over time such that it may be difficult to remember the correct point at which we resume a task after an interruption. Memory for Goals provides a process-level theory for why certain types of errors are made during a well-learned task as a consequence of retrospective, episodic memory (Altmann & Trafton, 2007; Ratwani & Trafton, 2010; 2011; Trafton, Altmann, & Ratwani, 2009).

In this report we describe how our postcompletion error model selected its actions and also explains sequence errors (perseverations and skips) in a story telling task. Some task-specific alterations were made (noted hence), but the general principles underlying our model allow it to work in this new domain without modification to its fundamentals. One can think of the the model as providing a highly specified template one can use to model action selection and error in any routine procedural task. It is a domain-specific mini-architecture built within the more general-purpose architecture of ACT-R.

General Principles of the Model

We learned the general principles enumerated below by using one model to explain one error type in two data sets, each having used a different experimental paradigm (Byrne & Bovair, 1997; Altmann, Trafton, & Ratwani, 2011). Our claim is that it is by the dynamic interaction of these principles that people select their actions in routine procedural environments. Perseverations and skips (postcompletion error is really just a skip that happens to occur in certain conditions) fall naturally out of the action selection process. This is because sometimes activations of correct and incorrect action representations become

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14. ABSTRACT
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comparable in strength and transient noise (a property of ACT-R) in that moment increases the wrong action's activation beyond the correct action's activation.

Spreading Activation

During normal operation the model selects the next step it will perform by retrieving a step from long-term memory. That retrieval process is driven by activation spreading from a task context representation it holds within its working memory. Each step representation is associated with all subsequent steps' representations by dividing the maximum allowable association (an ACT-R parameter) by the prospective distance from the current context to the subsequent step. E.G., the association from the current context to the next step is equal to the maximum association, from current to next +1 is 1/2 the maximum association (since the prospective distance is 2), etc. This is meant to implement a kind of step co-occurrence association proportional to how closely two steps occur with each other.

Strengthening

As in Memory for Goals, as the model performs each action it encodes an episodic memory of its current task context. That episodic memory's activation is strengthened at creation so that it is significantly higher than other, previous episodic memories which have already decayed to lower levels of activation. As in ACT-R's account of declarative long-term memory, the memory matching the retrieval request (e.g., for an episode) and with the highest activation at request time is the memory retrieved. Furthermore, retrieval of a memory strengthens its activation.

Functional Decay

As in ACT-R and Memory for Goals, the activation of a memory decays over time if it is not strengthened again by retrieval. Besides its implication in forgetfulness, decay serves a function (Altmann, 2002). When old memories decay, they allow new ones to start with activations which make them relatively more likely to be retrieved than the old ones. This prevents positive feedback loops when trying to remember different instances of the same kinds of information, such as episodic encodings.

Interruption and Resumption

The context we focus on is resuming after being interrupted. With the rapid rise of communication technologies that keep people accessible at all times, issues of interruptions and multitasking have become mainstream concerns. For example, Time magazine (Wallis, 2006) and the New York Times (Thompson, 2005) both reported stories about interruptions and multitasking and how they affect performance. The information technology research firm Basex issued a report on the economic impact of interruptions, which they estimated to be around $588 billion a year (Spira, 2005). Given the prevalence of interruptions, building systems that can help remind an individual what they were doing or where they were in a task can have a large impact on individual and group productivity.

Being interrupted also greatly increases the number of errors (Trafton, Altmann, & Ratwani, 2011). People will frequently repeat a step that has already been performed or skip a step that needs to be performed after an interruption. Sometimes these errors are irritating (e.g., destroying a meal by leaving out a crucial ingredient), but sometimes they can have disastrous consequences (e.g., taking medicine twice or not configuring the flaps for airplane takeoff). The research de- scribed here is applicable to these domains, but this report will focus on a common, everyday task: being interrupted while telling someone a story or giving instructions. This information-passing task is an excellent domain for studying the interruption/resumption process for several reasons. First, because it is so common to get interrupted while talking to a friend, it is easy to collect data. Second, providing ordered information to another person is a general class of problems that include recipes, checklists, story telling, direction giving, etc.

For example, in the middle of giving you instructions on how to operate a new device, your friend needs to take an important phone call for a few minutes. When she comes back to tell you the rest of the instructions, what does she do? If she cannot remember exactly where she left off, you may remind her or she may resume where she thought she left off (which may or may not be correct). If your friend was telling you a story, she may simply start somewhere close to where she left off. For the remainder of the paper, we will focus on building a process model of exactly what the interlocutor is doing as she attempts to resume the conversation, then we will relate elements of this model to our other attempts to build a unified process model of human routine procedural action selection and error.

The Story Telling Task

The important point of Trafton, Jacobs, and Harrison's experiment for this study's purposes was what it demonstrated about how people resume a task after being interrupted. Participants read three total pages of a soap-opera-like story, then retold the story to a confederate. After retelling approximately two-thirds of the story, participants in the interruption condition were interrupted by the experimenter at a predetermined location. The control condition served to verify that the location of the interruption was not an especially difficult part of the story.

Resumption lag was coded as the time from the end of the interruption (or the intended point of interruption in the control conditions) until the participants began to fluently resume the story. To code the location of the resumption, Trafton, Jacobs and Harrison coded the gist of the story around the interruption location, and marked it as either "repeat" (e.g., a gist utterance that was a repeat of what had already been said), "correct" (e.g., the next gist to occur in the story), or "skip" (e.g., an utterance that skipped the correct resumption gist). Experiment results will be presented in conjunction with model results.

Model Operation

Normal Task Execution

The model began each gist-telling cycle by retrieving from declarative memory a representation of one of the story's gists. This retrieval process was driven primarily by associative priming (empirically fit to a maximum of 1) from the model's active buffer contents. Then it updated its active buffer contents by copying the contents from its retrieved memory. Then the model spoke the contents of the gist. Next the model encoded an episodic memory with a reference to its active buffer contents, i.e., the gist it just spoke. Episodic encoding complete, the model repeated the cycle, beginning with the retrieval phase. In contrast to the Phaser and Financial Mangement tasks we modeled previously, we assume that the story telling task has a flat, rather than hierarchical goal structure, and the model's declarative memory encoding of the task reflects this.

Interruption

When the interruption began the model finished encoding its episodic representation as per normal operation. Then it cleared its active buffer contents and simply waited for 230 seconds, the average interruption duration (Trafton, Jacobs, & Harrison, 2012). The episodic memory's activation decayed during this interval using ACT-R's standard decay mechanism and default decay rate.

Resumption

When the interruption ended the model first tried to retrieve the episodic memory. If the episode's activation fell below a retrieval threshold (a feature of the ACT-R architecture, empirically fit to -2.375 for this model) it became unavailable to memory, and the model simulated asking for help. When the model did successfully retrieve the episode it then chose one of two competing resumption strategies it could employ: resume with the last gist told resume with the next gist.

We did this partly because we found that the model's associative action selection mechanism—a constraint provided by the model's performance of the form filling tasks described above—would not allow for sufficiently high levels of skips and repeats. In the form filling tasks we previously modeled repeats and skips occurred at rates well below 10%. Also we assume resumption place is subject to a sort of social mnemonic strategy people typically employ to remind the listener of a narrative's context. In fact, empirical testing led us to bias the model slightly in favor of this strategy. ACT-R's utility parameter for this strategy was 0.175 units higher than the resume-with-next strategy's while the standard deviation of the utility transient noise function was .1. This contrasts with Trafton et al.'s model which only tried to resume-with-next.

Here as in normal task execution the model relied upon priming by spreading activation to drive retrieval of a story gist. However, at resumption the model does not reconstruct its entire active buffer contents all at once, a feature hinted at by Trafton et al's findings regarding the time course of resumption from interruptions (Altmann & Trafton, 2007). This means that in absolute terms less activation was propagated to the gist retrieval process at the transition from resumption to the normal execution cycle. This lower ratio of associative signal to transient retrieval noise (0.25, the same value for this ACT-R parameter as in Trafton et al.' model) made skips more likely than during normal story telling because the difference in propagated activation between the current +1 gist's memory (the correct gist) and the current +2 gist's (the skip gist) memory was less relative to normal execution conditions. However, transient noise was, on average, the same. Therefore transient noise had a greater influence during resumption, and that made skips more likely than during normal execution. Sometimes when the model selected the "resume last gist" strategy it would skip, ultimately resulting in a "correct" resumption or even a skip. If it had selected the "resume next gist" strategy it was even more likely to ultimately skip.

This model is very different from Trafton, Jacobs, and Harrison's in when it encodes its episodic memories and how its process leads to skips. That model actually encodes its episodes after retrieval from declarative memory of the next gist to tell but *before* it has told the gist. An interruption may (or may not) fall between this episodic encoding and when a person has the chance to carry out an action. Therefore the model claims that in these cases people have a false memory of having carried out an action. This leads to the somewhat odd prediction that if an interruption could somehow be reliably timed to occur during action preparation—between episodic encoding and action performance—people will mostly perform skip errors at resumption rather than the correct action. When the interruption falls before the episodic encoding their model predicts that people will *never* skip at resumption.

The current model predicts skip rates to remain unchanged in such scenarios because they fall naturally out of the action selection mechanism. Preliminary results from another task in which subjects skip at a very small rate (1%) even when not interrupted match the model's rate for such trials. The increased skip rate at resumption comes from the juxtaposition of the action selection mechanism with this reduced active buffer content condition that occurs at resumption, a feature supported by Altmann and Trafton's (2007) findings.

Furthermore, Trafton, Jacobs, and Harrison's model, upon interruption, immediately stopped and switched tasks, predicting no switch lag for the interrupting task. The current model has so far been applied to tasks that interrupt immediately upon completion of an action. In this case, the model is just beginning its episodic encoding as the interruption starts. The model predicts switch lag for the interruption task is a consequence of this "finish up" activity left over from the previous action.

Model Fit

To reproduce the empirical data, we ran 2000 simulated trials with a (virtual) listener available. For modeling purposes we focus on time to continue after interruption and where resumption occurred. Participants asked for help or acted like they wanted some help 77% of the time. When the model attempted to retrieve an episodic code after the

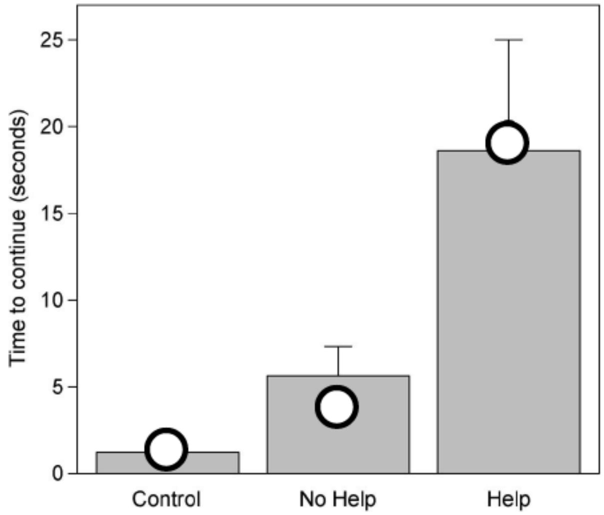

Figure 1. Resumption latencies of people (bars) and model fit (circles) in Trafton et al's story telling task. Error bars represent the 95% confidence interval.

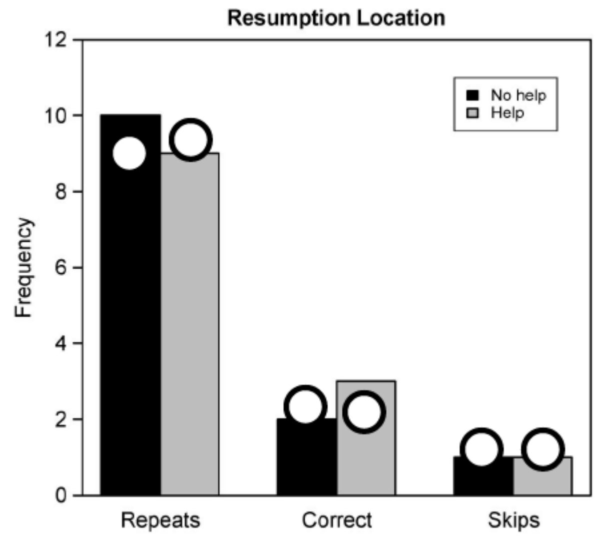

Figure 2. Where participants (bars) and the model (circles) resumed.

interruption, it failed and asked for help 79% of the time. When the model failed to resume on its own it was because transient noise made the episodic memory less active than the retrieval threshold The threshold functioned as a cut-off to abandon a retrieval when the amount of effort became excessive without leading to a successful retrieval. Trafton et al. did not match their model to control resumption latencies nor to where participants resumed. This model does match both in addition to the help and no help response latencies and help frequency.

Discussion

The novel contribution of our model stems from its generalizability. It went unchanged from postcompletion error in two form-filling tasks, each in different experimental paradigms, to sequence errors in story telling. The two form-filling tasks encouraged participant use of a hierarchical goal structure. The story telling task by contrast arguably let to flat goal structure. Yet despite the changes to task environment and type of error under examination, the general principles of the model—action selection by associative spreading activation based on step co-occurrence, strengthening, and functional decay—remained unchanged.

Generalization to Other Paradigms

Our model's account of sequence errors holds for computer tasks with hierarchical goal structures, as was used previously to study PCE. For example, Altmann, Trafton and Ratwani (2011) employed a type of form-filling task called the Financial Management Task. In this task participants filled out a form to buy or sell financial securities based on orders received. The task involved entering information from the orders into a series of interface elements such as pull-down menus, check boxes, and radio buttons. Elements were arranged into clusters of two to four elements all relating to one aspect of the order. There were ten such clusters in the interface and the task required participants to enter information into the clusters following a specific order.

Participants were interrupted occasionally while they performed this task. When they resumed the interface provided no cues to aid resumption at the correct next cluster Participants sometimes perseverated the last step they had performed or skipped the next step they were supposed to perform.

Perseveration Although the most recently-created episode, the one created for the action just performed, had the highest base level activation, at this point the previous episode, although decayed, was still more active than the background activation level. Transient noise occasionally caused previous episodic memories (usually the next most-recent) to be more active at that moment. Perseveration errors occurred here, when the model would retrieve an episode from one or two steps ago because of this combination of transient noise and the relative recency of the episode's creation did not allow decay quite enough time to reduce its activation far.

Unlike the story telling task's interruption, which involved declarative memory encoding of additional story, the financial management task's interruption task was to solve simple arithmetic problems for 15 seconds. We assume that some declarative rehearsal is possible during this time, perhaps interleaved with arithmetic operations as in Salvucci and Taatgen's theory of cognitive threading (Salvucci and Taatgen, 2008). A rehearsal cycle early during the interruption could retrieve one of these slightly older episodes as described above, strengthening that memory's activation Subsequent rehearsal cycles tended to strengthen whatever episode the model had retrieved at the onset of the interruption. At resumption the model would then load an

older, rather than the current, context into working memory and perseverate an older step.

Skips The model would perform skips in the financial management task for exactly the same reasons as in the story telling task. Associative priming from active buffer contents "bleeds over" from the intended target of declarative retrieval, the correct next step, to the step after that. This effect is magnified under conditions of degraded active buffer contents such as occurs during post-interruption resumption as in the financial management task or in high memory load as in Byrne and Bovair's Phaser task.

Potential Issues and Future Work

Although the story telling model presented here did not actually perform the interruption task, we believe the pertinent aspect of the interruption was simply that people did not engage in the primary task for some portion of time as a well-established and general mechanism, decay, explained this aspect of interruption and resumption performance. Future iterations of the model incorporate developments such as Salvucci and Taatgen's Threaded Cognition model to address issues such as what happens when interrupting tasks are complex and demanding, particularly of declarative memory.

We hope to apply the general principles learned from this model's development to difficult human-computer interaction problems. For example, our process model, for each potentially-retrieved memory for each declarative memory retrieval operation, produces a retrieval probability distribution. We can use this theoretically-derived data to build an action model for application in an autonomous teammate for a human. During task execution the robot builds a model of the human's cognitive state based on observed actions and known procedures. When the set of retrieval probability distributions indicates that the human's memory encoding the correct next task step is not clearly the most likely to be retrieved by the human then the robot intercedes to remind its human teammate of the correct task context. Human-robot interaction benefits because the robot uses the process model to "know" its human teammate like a human teammate would. This gives the robot the capability to know when help is needed, how to help, and how to otherwise remain unobtrusive. In other words, the robot would know when it would be a bad time to interrupt a person.

Example Application: An Autonomous Agent Sensitive to Interruption Costs

A human and a robotic teammate set out on a task. Both know the task. The robot observes its human teammate as they perform the task. The robot has a cognitive model of the task running and follows along, updating the model's state as the team performs the task. As in the model presented earlier in this paper, each step will involve a declarative retrieval of the relevant step memory and that means the robot's model contains the data necessary to predict the human's performance. We took that data and developed a classifier to predict whether or not a skip was imminent.

The variables that went into the logistic regression were the activations of the correct and next two gist memories as well as the amount of activation spread by the active buffer contents. As expected, the activation of the correct next gist memory and activation spreading from active buffer contents were highly negatively predictive of skip outcome while activations of the next two memories were highly positively predictive of skip outcome.

We then evaluated classifications of the logistic model using receiver-operating characteristic analysis. We determined the optimal decision criteria to be a skip probability of 33.5% which resulted in a true positive rate of 79.7% with a false positive rate of 0.9%, a d' of 3.17, and area under the ROC curve was 0.986. The area under the curve represents the probability that the logistic regression model will rank a randomly chosen positive instance (i.e. an error) higher than a randomly chosen negative instance (i.e. non-error) (Fawcett, 2006; Macmillan & Creelman, 2005). This is a quite high degree of discriminability and it means that when the decision model predicts a probability of skip of 33.5% or greater, the robot would successfully intervene in 79.7% of cases of when the human would have committed a skip error while only wrongly interrupting the human 0.9% of the time.

Conclusions

We started this project with our extant model of postcompletion error in two experimental paradigms, the Byrne and Bovair phaser task and the financial management task. This model contained a theory about how people select their actions when engaged in a routine procedural task because, we hypothesized, the same mechanisms underlying correct behavior must also cause errors. We tested the generalizability of our account by applying it to a new task domain and new error type, the story telling task and skip errors, respectively. The model's process worked very well for the story telling task. Furthermore, its mechanisms rooted in Memory for Goals (Altmann & Trafton, 2002) also provides an explanation for another type of error, perseveration.

We then applied data generated by the model to a binary classification problem: for a given point within a task, is a human likely to commit a skip error? We demonstrated that we can correctly predict the occurrence of skip errors in the model data with high accuracy. Furthermore, because our cognitive model performs so well across a variety of routine procedural tasks we strongly suspect that our classifier should perform well across that domain as well.

Future work may validate the classifier's performance for this story telling task. However the generalizability of the cognitive model upon which the classifier is based is what gives us hope for it one day being truly useful in the more general domain of routine procedural tasks. This includes many tasks in which one would want to use a robot—tasks that are dangerous, dirty, or dull—and especially tasks which demand human judgment but are improved with automated systems, such as transportation, chemical processing, and energy production, to name a few.

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